REVISIT OF MICROSCOPIC CAR FOLLOWING MODELS: CONVENTIONAL AND MACHINE LEARNING PERSPECTIVES

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Certificate of Original Authorship

I, Yang Yu declare that this thesis, is submitted in fulfilment of the requirements for the award of Doctor of Philosophy, in the Faculty of Engineering and Information Technology at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

This document has not been submitted for qualifications at any other academic institution.

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Abstract

Microscopic car following models, or simply car following models, are used to determine how vehicles are following one another on roadways. They are the foundation of microscopic traffic flow theories and are of great importance with regard to the developments of adaptive cruise control (ACC) system and connected and automated vehicles (CAV), as well as the evaluation of intelligent transportation system (ITS) strategies. Therefore, it is very demanding to keep improving existing car following models or develop new ones towards better reproducing human driver behaviours or addressing specific traffic challenges. In this thesis, we mainly focus on conventional, mathematical-equation based car following models and novel, machine-learning based car following models.

The aims and purposes of this thesis consist of five folds: 1) to take intensive revisits into several widely-used microscopic car following models (from conventional model family or machine-learning based model family) to further study their advantages and deficiencies; 2) to propose corresponding solutions (by modifying car following model structure or model calibration approach) towards addressing such deficiencies of existing models; 3) to develop new car following models using novel machine learning technologies to solve traffic challenges that human drivers are hard to overcome; 4) to comprehensively evaluate the performances of the proposed car following models by comparing them with similar, existing counterparts from various aspects; 5) to discuss about the application fields where these proposed car following models can be best applied.

To achieve the above goals, in the first part of the thesis (Chapter 3 and 4), we mainly focus on the revisiting of conventional, equation-based car following models. Firstly, we revisit a well-recognised conventional car following model and find that this model may easily yield overreacted outputs in specific conditions, especially in face of the changes of leaders that are widely seen on multi-lane roadways. Then, we improve the model by introducing a dynamic acceleration confinement term to ensure that under no circumstances will the model produce any overreacted maneuvers. Experimental results also validate that the modified car following model can indeed better reproduce human driver behaviours in the aforementioned scenarios and it can be applied to both single-lane scenarios and multi-lane scenarios. Secondly, we also pay attention to the parameter calibration process of conventional car following models. Different from the previous attempt which optimizes conventional models through modifying

model structures, we alternatively try to improve conventional models towards solving specific traffic challenges (e.g. achieve eco-driving) through the modification of model parameter calibration approaches.

In the second part of the thesis (Chapter 5 and 6), we transfer our focus to modelling car following maneuvers using machine learning technologies. To be specific, two novel car following models based on different cutting-edge machine learning algorithms have been proposed, respectively. The first model is built on one of the popular reinforcement learning algorithms and aims at jointly improving travel efficiency and reducing energy consumption. Due to the physical limitations and selfishness (uncooperativeness) of human drivers, it is very difficult for human driven vehicles to achieve the above dual goals. Therefore, the first car following model is designed dedicated for connected and automated vehicles. By contrast, the second car following model is developed from a simple lazy-learning algorithm that enables the model to learn from the massive field traffic data to better reproduce different human driver behaviours in a real-time manner. The birth of the model is a result of an intensive revisit into an existing field-data driven car following model that performs well in general yet still has a few obvious deficiencies including low computational efficiency and prediction accuracies being easily interfered by non-similar field data samples. By introducing a different lazy-learning algorithm, the new model can perfectly address the aforementioned deficiencies of the existing model. A series of experimental tests (case studies) have also been conducted to validate the performances of the two machine-learning based car following models proposed in this thesis.

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List of Abbreviations and Mathematical Notations

$x_n(t)$	position of the n^{th} following vehicle in a platoon at time t
$\dot{x}_n(t)$	speed of the n^{th} following vehicle in a platoon at time t
$\ddot{x}_n(t)$	acceleration of the n^{th} following vehicle in a platoon at time t
x	position of a vehicle
v	speed of a vehicle
Δx	the space headway between a following vehicle and its immediate leader
Δv	the speed difference between a leader and its immediate follower
$V(\Delta x)$	the function to decide the current optimal speed for all car following models in the Optimal Velocity car following model (OV model) family
τ	the relaxation time of (the driver of) the following vehicle with regard to adapting to the optimal speed
$\lambda\ or\ \kappa$	following vehicle's response sensitivity coefficient to speed difference Δv
l	average length of a vehicle
$V_1 + V_2$	the maximum desired speed under free-flow traffic conditions of the optimal velocity function $V(\Delta x)$
l_{int}	the interaction length that decides the transition regime for the S-shaped curve of the optimal velocity function $V(\Delta x)$
β	a unitless parameter that decides the shape of the equilibrium fundamental diagram for all car following models in the OV model family
a_{cap}	a high acceleration rate that most real vehicles can reach and most drivers would be able to maintain while still safely controlling the vehicle
d_{cap}	a strong deceleration rate that most real vehicles can reach and most drivers would be able to maintain while still safely controlling the vehicle
a_{max}	the (average) maximum acceleration limit of modern vehicles
d_{max}	the (average) maximum deceleration limit of modern vehicles

r^{+}	reduction degree parameter of the confined Full Velocity Difference car following model (c-FVD model) to modify any overshooting accelerations
r^{-}	reduction degree parameter of the c-FVD model to modify any overshooting decelerations
r_{ini}^{-}	the initial value of the deceleration reduction degree parameter r^{-}
F_{mix}	mixed error measure
F_{abs}	absolute error measure
$\langle X \rangle$	the temporal average value of the variable X over the whole time duration
$\lvert X \rvert$	the absolute value of variable X
$\dot{X}$	the first order derivative of variable X
$\ddot{X}$	the second order derivative of variable X
$\lfloor X \rfloor$	the truncated value of variable X
δ_t	the delay time of vehicle motion in a platoon
c_j	the kinematic wave speed at jam density in a platoon
N	the population of each generation in the genetic algorithm
Pb_m	the mutation probability of a single individual in the genetic algorithm
v_{limit}	the speed limit (maximum safe speed) of a vehicle
Δx_{max}	the maximum allowable space headway used in the modified genetic algorithm calibration method
Δx_{min}	the minimum safe space headway used in the modified genetic algorithm calibration method
hw_{max}	the maximum allowable time headway used in the modified genetic algorithm calibration method
hw_{min}	the minimum safe time headway used in the modified genetic algorithm calibration method
$e_{penalty}$	the fixed, heavy fuel consumptions used as a penalty in the modified genetic algorithm calibration method

v_0	the desired speed of a following vehicle in the Intelligent Driver Model (IDM)
T	the safe time headway of a following vehicle in the IDM
a	the maximum acceleration of a following vehicle in the IDM
b	the desired deceleration of a following vehicle in the IDM
δ	the acceleration exponent of the IDM
s_0	the jam distance in the IDM
m	the mass of a vehicle
A_f	the frontal area of a vehicle
C_r	the rolling resistance of vehicle tyre with road surface
C_D	the aerodynamic drag coefficient of a vehicle
ρ_{air}	the air mass density
g	the gravitational acceleration
α	the road slope
U	the rated battery voltage of an electric vehicle
Q	the rated battery capacity of an electric vehicle
η_m	the electric motor (battery cell) efficiency of an electric vehicle
η_g	the generator efficiency of an electric vehicle with energy regenerative brakings
$F_{air}(t)$	the air drag force of a vehicle at time t
$F_r(t)$	the rolling resistance force of a vehicle at time t
$F_G(t)$	the gravity force of a vehicle at time t
$p_b(t)$	the instant power output or instant recovered energy input at time t
τ	the updating interval of the Fixed Radius Near Neighbours car following model (FRNN model) and K Nearest Neighbours car following model (KNN model)
$s^{t-\tau}$	the space headway of the following vehicle at time $t-\tau$ in FRNN model
s^t	the space headway of the following vehicle at time t in FRNN model

lmd^t the moving distance of the immediate leader during a single updating interval at time t in FRNN model

$lmd^{t+\tau}$ the moving distance of the immediate leader during a single updating interval at time $t+\tau$ in FRNN model

$sd_{s^{t-\tau}}$ the standard deviation of input feature $s^{t-\tau}$ that are derived based on that feature of all historical vehicle samples in the historical traffic dataset in FRNN model

sd_{s^t} the standard deviation of input feature s^t that are derived based on that feature of all historical vehicle samples in the historical traffic dataset in FRNN model

sd_{lmd^t} the standard deviation of input feature lmd^t that are derived based on that feature of all historical vehicle samples in the historical traffic dataset in FRNN model

$sd_{lmd^{t+\tau}}$ the standard deviation of input feature $lmd^{t+\tau}$ that are derived based on that feature of all historical vehicle samples in the historical traffic dataset in FRNN model

md^t the moving distance of a vehicle during a single updating interval at time t in FRNN model

$D(i,o)$ the scaled Euclidean distance in terms of four input features between following vehicle i and following vehicle o in FRNN model

$O(X)$ the big O notation to classify algorithms based on how their run time grow as the input size grows

n the size of historical traffic dataset (training dataset) used by FRNN model

d the dimensions (numbers) of input features of each vehicle sample in the historical traffic dataset used by FRNN model

k the number of similar historical vehicle samples the KNN model or FRNN model would adopt

R the main fixed radius used by FRNN model to filter non-similar historical vehicle samples based on the scaled Euclidean distance

r the second radius used by FRNN model to further guarantee model prediction accuracy

u the (average) speed of the vehicles on a roadway segment

k the traffic density of a roadway segment

q the traffic flow of a roadway segment

u_o the optimal speed of a roadway segment

k_o the optimal traffic density of a roadway segment

q_{max} the capacity (maximum traffic flow) of a roadway segment

u_f the free flow speed of a roadway segment

k_j the jam density of a roadway segment

List of Publications

Below is a list of publications that are included in this thesis as Chapter 3, 4, 5, 6, and Appendix 1, respectively. All publications are co-authored with other researchers.

Chapter 3:

Yang Yu, Rui Jiang, Xiaobo Qu*. 'A Modified Full Velocity Difference Model with Acceleration and Deceleration Confinement: Calibrations, Validations, and Scenario Analyses' [J]. *IEEE Intelligent Transportation Systems Magazine.* Status: Published.

Chapter 4:

Yang Yu, Xiaobo Qu*. 'Development of Parametric Eco-Driving Models for Fuel Savings: A Novel Parameter Calibration Approach' [J]. *International Journal of Transportation Science and Technology.* Status: Under review.

Chapter 5:

Xiaobo Qu, Yang Yu, Mofan Zhou, Chin-Teng Lin, Xiangyu Wang*. 'Jointly Dampening Traffic Oscillations and Improving Energy Consumption with Electric, Connected and Automated Vehicles: A Reinforcement Learning Based Approach' [J]. *Applied Energy*. Status: Published.

Chapter 6:

Yang Yu, Zhengbing He, Xiaobo Qu*. 'On the Impact of Prior Experiences in Car Following Models: Model Development, Computational Efficiency, Comparative Analyses and Extensive Applications' [J]. *IEEE Transactions on Cybernetics*. Status: Under review.

Appendix 1:

Yang Yu*, Yun Zou, Xiaobo Qu. 'To investigate the hidden gap between traffic flow fundamental diagrams and the derived microscopic car following models: A theoretical analysis' [C]. *KES International Symposium on Smart Transportation Systems 2020*. Status: Published.

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